Generative Recommendation with Semantic IDs:
A Practitioner's Handbook

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Abstract

Generative recommendation (GR) has gained increasing attention for its promising performance compared to traditional models. A key factor contributing to the success of GR is the semantic ID (SID), which converts continuous semantic representations (e.g., from large language models) into discrete ID sequences. This enables GR models with SIDs to both incorporate semantic information and learn collaborative filtering signals, while retaining the benefits of discrete decoding. However, varied modeling techniques, hyper-parameters, and experimental setups in existing literature make direct comparisons between GR proposals challenging. Furthermore, the absence of an open-source, unified framework hinders systematic benchmarking and extension, slowing model iteration. To address this challenge, our work introduces and open-sources a framework for **G**enerative **R**ecommendation with semantic **ID**, namely GRID, specifically designed for modularity to facilitate easy component swapping and accelerate idea iteration. Using GRID, we systematically experiment with and ablate different components of GR models with SIDs on public benchmarks. Our comprehensive experiments with GRID reveal that many overlooked architectural components in GR models with SIDs substantially impact performance. This offers both novel insights and validates the utility of an open-source platform for robust benchmarking and GR research advancement. GRID is open-sourced at https://github.com/snap-research/GRID.

1 Introduction

Recommender systems (RecSys) are essential in improving users' experiences on web services, such as product [21, 48], video [14, 22], friend [25, 28, 47] recommendations. Among all RecSys, Generative Recommendation (GR) is a rapidly growing paradigm [33, 44, 66, 68], due to recent successes of generative models in vision [9, 16, 17] and language [1, 3, 15, 24, 63]. GR leverages advancements in generative models, such as directly generating texts of items of interest [2, 12, 19, 51] or extracting semantic representations from pre-trained models that encode open-world knowledge [45, 61, 64].

Within GR, one popular paradigm explores Semantic IDs (SIDs) [7, 44, 61] to bridge the gap between pre-trained foundation models and RecSys. As shown in Figure 1, this paradigm first harnesses a modality encoder and a quantization tokenizer (e.g., RQ-VAE [31], VQ-VAE [10], or Residual K-means [7]) to transform the modality features (e.g., image or text) into SIDs. A sequential recommender is then trained to autoregressively predict SIDs of future items users will interact with given past items' SIDs.

GR with SIDs provides an effective way to leverage both semantic knowledge encoded in pre-trained foundation models as well as collaborative signals encoding in the user-item interaction history: the overlap in SIDs of two items in principle reflects their semantic similarity, and next-item supervision allows the GR model to learn collaborative signals across SIDs. Since the introduction by [44], researchers have proposed multiple variants of GR models with SIDs [7, 41, 42, 61], several of which advance performance or demonstrate deployment in production systems.

Despite this promising progress, further development of GR with SIDs faces several challenges. First, *most relevant literature does not provide open-source implementations*. This challenge leaves practitioners and researchers to undertake complicated re-implementation burdens, requiring not only advanced technical expertise but also careful hyperparameter tuning. This challenge can be further aggravated by the complexity nature of GR pipelines with SIDs. As we will show later in this paper, good performance of GR pipelines is usually determined by multiple confounding factors at the same time (e.g., appropriate training strategies and careful architecture tuning). When building a GR pipeline with SIDs from scratch, it is extremely difficult to debug and pinpoint root causes of potential sub-optimal performance, significantly slowing research and development velocity. Furthermore, *useful insights around design choices for GR with SIDs are typically not well-discussed in the literature*, leaving practitioners to spend valuable time and computational resources building their own experimental pipelines to develop these understandings on their own. To bridge these gaps, we make the following contributions:

- We present GRID, an easy-to-use, flexible, and efficient playground for rapid prototyping of GR with SID methods. GRID includes rigorous implementations of fundamental components in GR with SID (e.g., Semantic ID tokenizer, sequential recommender, etc) and can be easily extended to incorporate ongoing efforts in the GR space. To our knowledge, GRID is the first open-source resource for prototyping GR with SIDs that can reproduce results reported in existing literature.
- Using GRID, we conduct comprehensive experiments to study the impacts of various components in the GR with SID paradigm. Our results include several surprising observations which shed light on key modeling and algorithmic trade-offs that have thus far been mostly overlooked in existing literature.

2 Related Work

Semantic ID. RecSys performance hinges on learning quality representations [5, 23, 27, 29, 37, 67]. Standard practice assigns unique, uninformative IDs to users/items, mapping them to embeddings that capture collaborative signals [36, 39, 46, 58, 59, 64]. This approach struggles with scalability [13, 58, 65] and performance in

(a) _Overarching Architecture of GRID_

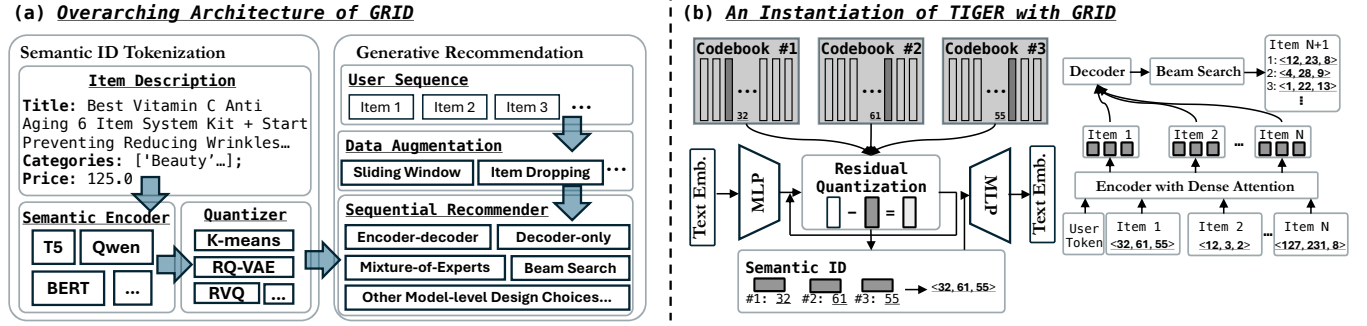**(b)** _An Instantiation of TIGER with GRID_

Figure 1: (a) The overarching architecture of GRID. GRID modularizes all intermediate steps in the workflow of GR with SIDs to accelerate the pace of innovation. (b) Instantiating TIGER [44] with GRID is straightforward, as it is simply specifying several components already available within GRID, offering practitioners a reliable reference implementation to build on top of.

sparse or long-tail settings [23, 32, 36, 37, 49, 55]. Semantic IDs (SIDs) address these issues by encoding semantic features (e.g., text) via modality encoders (e.g., LLMs), followed by quantization of dense embeddings into sparse IDs [44, 50, 51]. Common quantization-based tokenizers include RQ-VAE [31], RVQ [54], and Residual K-Means [7].

Generative Recommendation with SID. TIGER [44] first applied transformers to predict item SIDs for recommendation, extending ideas from GR in document retrieval [52]. Follow-up work improves SID training via collaborative signals [4, 34, 57, 60, 69, 70, 72], distributional balancing [30, 62], and advanced LLMs or multimodal encoders [20, 35, 40, 51, 61, 73]. Yet, the field lacks a unified, open-source framework. We address this gap by releasing GRID, a modular toolkit to streamline and accelerate GR experimentation.

3 Proposed Framework: GRID– Generative Recommendation with Semantic IDs

We consider a set of users $\mathcal{U}$ interacting with items in $\mathcal{I}$. Each item $i \in \mathcal{I}$ has associated semantic features $\mathbf{f}_i$, including but not limited to text and image. Each user $u \in \mathcal{U}$ has an interaction sequence of length L_u, denoted as $\mathcal{S}_u = [i_1^u, i_2^u, \cdots, i_{L_u}^s]$. Without loss of generality, a modality encoder (e.g., LLM or VLM) $E(\cdot) : \mathbf{f} \to \mathbb{R}^d$ transforms $\mathbf{f}_i$ into a d-dimensional representation $\mathbf{h}_i \in \mathbb{R}^d$. GR aims to solve the sequential recommendation task, where given a user sequence $\mathcal{S}_u$, GR frameworks generate candidate(s) for the item that the given user will interact with next (i.e., $i_{L_u+1}^s$).

3.1 Architecture: Tokenization-then-Generation

GRID splits of GR with SIDs into two separate phases: tokenization-then-generation, adopting the common pattern (see Figure 1). During tokenization, GRID maps item embeddings (i.e., $\mathbf{h}_i$) into SIDs. During generation, with SIDs for all items, GRID explores generative model architectures (e.g., transformer-based models) to generate the SID of $i_{L_u+1}^s$. GRID provides flexible implementations for components at each stage.

Semantic ID Tokenization. SID tokenization entails first computing embeddings $\mathbf{h}_i$ of items' semantic features with a pre-trained modality encoder $E(\cdot)$, then mapping these embeddings to sequences of sparse IDs via a hierarchical clustering tokenizer. The hierarchical

organization of SID enables precise granularity control via diverse prefix levels. Formally, given $\mathbf{h}_i$, a tokenizer $\text{Tokenizer}(\cdot) : \mathbb{R}^d \to \{0, 1, \cdots, W\}^L$ maps item embedding $\mathbf{h}_i$ into a sequence of ID, formulated as $\text{SID}_i = \text{Tokenizer}(\mathbf{h}_i) = [\text{SID}_i^0, \text{SID}_i^1, \cdots, \text{SID}_i^L]$, where W refers to the cardinality of each ID and L denotes the number of hierarchies. GRID offers plug-and-play modules for computing $\mathbf{h}_i$, making the swapping of $E(\cdot)$ straightforward – practitioners can either import customized models or use existing models available on HuggingFace[1]. For the tokenizier, GRID supports three algorithms: Residual Mini-Batch K-Means (RK-Means [7, 38]), Residual Vector Quantization (R-VQ [10]), and Residual Quantized Variational Autoencoder (RQ-VAE [31]). For instance, as shown in Figure 1, the tokenization phase of TIGER [44] can be constituted by specifying a T5 encoder to generate item representations, followed by training a RQ-VAE to generate SIDs, all with few-line configuration changes.

Next Item Generation. With SIDs generated for all items, for each user sequence, GR frameworks leverage a sequential model to generate a list of candidate items that the given user is most likely going to interact with. In GRID, we incorporate both encoder-decoder [8, 43, 56] and decoder-only [1, 3, 53] model architectures with flexible configurations (e.g., the number of heads, layers, or mixture-of-experts in transformer layers). As for tokenization, practitioners can easily import custom architectures or borrow model architectures publicly available in HuggingFace. By default, we train the generation model using the commonly adopted next-token prediction objective [26, 44] with sliding window augmentation [71][2]. The inference generation is conducted through beam search with KV-cache, with tunable hyper-parameters such as beam width, whether search is restricted to valid SIDs, etc. We also provide implementations for several tricks broadly explored in existing literature to showcase GRID's flexibility, including user token [44], and de-duplication of SID to avoid collision.

4 Experiments with GRID

We next showcase GRID's utility by conducting a brief, but rigorous, investigation into the performance trade-offs around several fundamental, yet overlooked, design choices within GR with SID.

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[1]https://huggingface.co/docs/transformers
[2]Training and inference logic can be fully customized.

Table 1: Performance of GR models with by SIDs generated by different tokenization algorithms.

Methods	Recommendation Performance (Recall@5/Recall@10/NDCG@5/NDCG@10)											
	Beauty				Toys				Sports			
RK-Means	**0.0422**	**0.0639**	0.0277	0.0347	**0.0376**	**0.0577**	**0.0243**	**0.0308**	**0.0236**	**0.0353**	**0.0153**	**0.0191**
R-VQ	**0.0422**	0.0638	**0.0282**	**0.0351**	0.0327	0.0493	0.0209	0.0262	0.0234	0.0352	0.0151	0.0189
RQ-VAE	0.0404	0.0593	0.0268	0.0329	0.0342	0.0514	0.0224	0.0280	0.0205	0.0312	0.0132	0.0166

Table 2: Performance of GR models with SIDs generated by RK-Means with varying-size language model encoders.

LM	Recommendation Performance (Recall@5/Recall@10/NDCG@5/NDCG@10)											
	Beauty				Toys				Sports			
L	**0.0429**	0.0639	**0.0285**	**0.0353**	0.0373	0.0565	0.0237	0.0300	0.0224	0.0347	0.0145	0.0185
XL	0.0422	0.0639	0.0277	0.0347	0.0376	0.0577	0.0243	0.0308	0.0236	0.0353	0.0153	0.0191
XXL	**0.0429**	**0.0646**	0.0282	0.0352	**0.0381**	**0.0586**	**0.0245**	**0.0311**	**0.0239**	**0.0363**	**0.0154**	**0.0194**

Table 3: Beauty GR performance with RK-Means SIDs with varying codebook dimensions from Flan-T5-XL embeddings.

$L \times W$	Recall@5	Recall@10	NDCG@5	NDCG@10
3×128	0.0412	0.0617	0.0273	0.0339
3×256	**0.0422**	**0.0639**	**0.0277**	**0.0347**
3×512	0.0415	0.0631	0.0273	0.0342
2×256	0.0403	0.0618	0.0264	0.0333
4×256	0.0405	0.0609	0.0265	0.0331
5×256	0.0396	0.0596	0.0257	0.0321

Table 4: GR performance on Beauty with varying number of TIGER [44]-style user tokens.

# Tokens	Recall@5	Recall@10	NDCG@5	NDCG@10
0	**0.0408**	**0.0618**	**0.0270**	0.0330
2,000	0.0396	0.0597	0.0264	0.0328
4,000	0.0401	0.0612	0.0264	0.0332
6,000	0.0401	0.0611	0.0264	0.0331
8,000	0.0405	0.0610	0.0269	**0.0335**

Setup. We evaluate on 5-core filtered Amazon Beauty, Sports, and Toys datasets [18, 44], using the last item per user for test, second-to-last for validation, and the rest for training. Item text features include Title, Categories, Description, and Price. Semantic embeddings are extracted via mean pooling over final hidden states of Flan-T5-Large, XL, and XXL [6]. For tokenization, we consider RK-Means [7], R-VQ [10], and RQ-VAE [31]. For generation, we analyze architectural choices mentioned above. Tokenizers are trained on 8 GPUs with per-device batch size 2048. RK-Means and R-VQ are trained layer-wise for 1k steps per layer; RQ-VAE for 15k total steps. The learning rate (LR) is 10^{-3} with Adam (R-VQ) or Adagrad (RQ-VAE). Residuals are normalized (RK-Means, R-VQ) and embeddings whitened (RQ-VAE) to prevent collapse. Generative models use Adam with LR 5×10^{-4}, weight decay 10^{-6}, and batch size 256. We use sliding-window sampling [40], with early stopping after 10 validation intervals (100 steps each) without NDCG@10 improvement. For model architectures of generative models, we explore 8 transformer layers in total (i.e., 4 in the encoder and 4 in the decoder for encoder-decoder models) with 6 attention heads in each layer, an embedding dimension of 128, and 1024 hidden dimensions for MLP layers. We report Recall@K and NDCG@K for $K \in 5, 10$ on the test set, using the checkpoint with best validation Recall@10. All results are averaged over 5 runs with different seeds.

4.1 Semantic ID Tokenization

We study SID tokenization by ablating (1) the choice of SID tokenizer algorithm, (2) the size of the pre-trained semantic encoder, and (3) the number of residual layers (i.e., L) and tokens per layer (i.e., W) in the SID tokenizer. We train variants of SID tokenizers and evaluate the performance of the base sequential recommendation

model trained using the corresponding tokenizer. Unless otherwise noted, we use RK-Means with $(L, W) = (3, 256)$ and Flan-T5-XL.

SID Tokenizer Algorithm. RQ-VAE is commonly adopted in the literature as the default SID tokenizer [41, 50, 62, 68] since its use by TIGER [44]. However, it entails simultaneously training an autoencoder and quantizer, exacerbating a number of challenges [11, 30, 74] and raising the question of whether its performance benefits are worth the implementation complexity. Table 1 suggests the answer is "no": RK-Means and sometimes R-VQ lead to better recommendation performance than RQ-VAE, despite our training of RQ-VAE for 5x as many iterations as the simpler alternatives.

Semantic Encoder Size. We next vary the size of the Flan-T5 model [6] used to compute the semantic embeddings, from Large (780M parameters) to XL (3B) to XXL (11B). Table 2 shows only marginal increases in recommendation performance due to an over 14-fold increase in the number of LLM parameters, indicating that the current GR with SID pipeline can be improved by more fully leveraging the increased world knowledge in larger LLMs.

SID Tokenizer Dimension. In Table 3, we vary the number of residual layers L and tokens per layer W in RK-Means, and observe that the default choice of $(L, W) = (3, 256)$ leads to the best recommendation performance. Surprisingly, performance drops substantially with more layers, although additional layers convey more semantic information to the recommendation model. This points to a trade-off between SID sequence learnability and the amount of semantic information contained in the SIDs.

4.2 Generative Recommendation

To understand the impact of next-item generation model design choices, we ablate the: (1) quantity of user tokens, (2) choice between encoder-decoder and decoder-only architectures, (3) integration of data augmentation for training, (4) implementation of

Table 5: GR performance with different architectures.

Model	Recall@5	Recall@10	NDCG@5	NDCG@10
	Beauty			
Enc-Dec	**0.0396**	**0.0597**	**0.0264**	**0.0328**
Dec-only	0.0300	0.0438	0.0206	0.0251
	Toys			
Enc-Dec	**0.0357**	**0.0548**	**0.0226**	**0.0287**
Dec-only	0.0286	0.0399	0.0202	0.0238
	Sports			
Enc-Dec	**0.0192**	**0.0290**	**0.0124**	**0.0156**
Dec-only	0.0152	0.0226	0.00979	0.0121

Table 6: GR performance with, without data augmentation.

Augmentation	Recall@5	Recall@10	NDCG@5	NDCG@10
	Beauty			
Sliding Window	**0.0396**	**0.0597**	**0.0264**	**0.0328**
No Augmentation	0.0279	0.0447	0.0171	0.0226
	Toys			
Sliding Window	**0.0357**	**0.0548**	**0.0226**	**0.0287**
No Augmentation	0.0277	0.0442	0.0173	0.0226
	Sports			
Sliding Window	**0.0192**	**0.0290**	**0.0124**	**0.0156**
No Augmentation	0.0174	0.0250	0.0114	0.0140

Table 7: GR performance with, without SID de-duplication.

Approach	Recall@5	Recall@10	NDCG@5	NDCG@10
	Beauty			
With De-dup.	**0.0396**	**0.0597**	**0.0264**	**0.0328**
No De-dup.	0.0381	0.0591	0.0253	0.0321
	Toys			
With De-dup.	**0.0357**	**0.0548**	**0.0226**	**0.0287**
No De-dup.	0.0353	0.0532	0.0225	0.0282
	Sports			
With De-dup.	**0.0192**	**0.0290**	**0.0124**	**0.0156**
No De-dup.	0.0186	0.0269	0.0011	0.0142

Table 8: GR performance with different beam searches.

Approach	Recall@5	Recall@10	NDCG@5	NDCG@10
	Beauty			
Constrained	0.0396	0.0597	0.0264	0.0328
Free-form	**0.0405**	**0.0609**	**0.0268**	**0.0334**
	Toys			
Constrained	**0.0357**	**0.0548**	0.0226	0.0287
Free-form	0.0356	0.0546	**0.0227**	**0.0289**
	Sports			
Constrained	0.0192	0.0290	0.0124	0.0156
Free-form	**0.0198**	**0.0302**	**0.0127**	**0.0160**

de-duplication IDs, and (5) employment of constrained or unconstrained beam search. We employ the default SID tokenization described previously and evaluate next-item generation performance.

The Quantity of User Tokens. TIGER [44] prepends a user token to every user's SID sequence, where user tokens are assigned via a random hash into a fixed vocabulary size. Table 4 reveals that a larger user token vocabulary does not always improve performance and totally removing this design (i,.e., 0) leads to the optimal performance, implying that the current standard use of user tokens in GR with SIDs is not achieving its goal of personalization.

Encoder-decoder vs. Decoder-only Architecture. Most existing literature explores encoder-decoder based transformer generative models [44, 61]. To investigate the feasibility of decoder-only architecture, we swap the encoder-decoder backbone with a decoder-only architecture. As shown in Table 5, decoder-only models significantly under-perform encoder-decoder models. We hypothesize that this substantial performance gap can be attributed to the inherent design of encoder-decoder models, where the encoder's dense attention mechanism over the entire user history effectively captures richer and more comprehensive sequential patterns. This deep contextual understanding, subsequently leveraged by the decoder for generation, appears to be critical for the challenging task of generative recommendation.

Data Augmentation for Training. In Table 6, we study the impact of data augmentation on the performance of GR with SIDs. We explore sliding window data augmentation, where a single user sequence is expanded into all possible contiguous sub-sequences [71]. Our observations strongly indicate that proper data augmentation is paramount for achieving robust and high-performing GR models. The expanded and varied training samples generated through this technique likely enhance the model's ability to learn more generalizable patterns from user interactions, mitigate overfitting, and improve its capacity to predict diverse next items, even in the presence of noisy and/or sparse data.

De-duplication of SIDs. De-duplicating SIDs is essential for accurate retrieval. We compare two strategies: TIGER's method, which appends a digit to SIDs to resolve collisions ("With De-dup."), and a simpler approach of randomly selecting an item when SIDs conflict. Table 7 shows both perform comparably, with TIGER's strategy having a slight edge. However, TIGER's approach increases sequence length and decoding complexity, and its requirement for global SID distribution knowledge is impractical for large item sets.

Constrained vs. Unconstrained Beam Search. Decoding strategy impacts both generation quality and computational efficiency. Our ablation study compares constrained and unconstrained beam search, vital for generative recommender system deployment. While constrained beam search guides output to valid SIDs, unconstrained explores all sequences without explicit rules. Table 8 shows both yield similar performance. Crucially, unconstrained beam search was significantly more efficient and computationally cheaper. This suggests the SID generation task's inherent structure, combined with learned model patterns, is sufficient for high-quality recommendations without the overhead of explicit constraints.

5 Conclusion

In this work, we highlight the critical need for a unified open-source framework in GR with SIDs. Through GRID, we conduct systematic experiments, revealing multiple surprising insights. We discover that several components previously assumed essential—and which are often compute- and/or engineering-intensive—can actually be replaced with more efficient alternatives without sacrificing performance. Conversely, other, often overlooked design choices prove to be vital, such as encoder-decoder architectures and data augmentation. These findings not only offer novel insights into the true drivers of GR with SID performance but also underscore the immense value of an open-source platform like GRID for robust benchmarking and accelerating research.

References

[1] Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. 2023. Qwen technical report. *arXiv preprint arXiv:2309.16609* (2023).

[2] Keqin Bao, Jizhi Zhang, Yang Zhang, Wenjie Wang, Fuli Feng, and Xiangnan He. 2023. Tallrec: An effective and efficient tuning framework to align large language model with recommendation. In *Proceedings of the 17th ACM Conference on Recommender Systems*. 1007–1014.

[3] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems* 33 (2020), 1877–1901.

[4] Runjin Chen, Mingxuan Ju, Ngoc Bui, Dimosthenis Antypas, Stanley Cai, Xiaopeng Wu, Leonardo Neves, Zhangyang Wang, Neil Shah, and Tong Zhao. 2024. Enhancing item tokenization for generative recommendation through self-improvement. *arXiv preprint arXiv:2412.17171* (2024).

[5] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, et al. 2016. Wide & deep learning for recommender systems. In *Proceedings of the 1st workshop on deep learning for recommender systems*. 7–10.

[6] Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Yunxuan Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. 2024. Scaling instruction-finetuned language models. *Journal of Machine Learning Research* 25, 70 (2024), 1–53.

[7] Jiaxin Deng, Shiyao Wang, Kuo Cai, Lejian Ren, Qigen Hu, Weifeng Ding, Qiang Luo, and Guorui Zhou. 2025. Onerec: Unifying retrieve and rank with generative recommender and iterative preference alignment. *arXiv preprint arXiv:2502.18965* (2025).

[8] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers)*. 4171–4186.

[9] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. 2020. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929* (2020).

[10] Patrick Esser, Robin Rombach, and Bjorn Ommer. 2021. Taming transformers for high-resolution image synthesis. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 12873–12883.

[11] Christopher Fifty, Ronald G Junkins, Dennis Duan, Aniketh Iyengar, Jerry W Liu, Ehsan Amid, Sebastian Thrun, and Christopher Ré. 2024. Restructuring vector quantization with the rotation trick. *arXiv preprint arXiv:2410.06424* (2024).

[12] Shijie Geng, Shuchang Liu, Zuohui Fu, Yingqiang Ge, and Yongfeng Zhang. 2022. Recommendation as language processing (rlp): A unified pretrain, personalized prompt & predict paradigm (p5). In *Proceedings of the 16th ACM conference on recommender systems*. 299–315.

[13] Benjamin Ghaemmaghami, Mustafa Ozdal, Rakesh Komuravelli, Dmitriy Korchev, Dheevatsa Mudigere, Krishnakumar Nair, and Maxim Naumov. 2022. Learning to Collide: Recommendation System Model Compression with Learned Hash Functions. *ArXiv* abs/2203.15837 (2022). https://api.semanticscholar.org/CorpusID:247794181

[14] Carlos A Gomez-Uribe and Neil Hunt. 2015. The netflix recommender system: Algorithms, business value, and innovation. *ACM Transactions on Management Information Systems (TMIS)* (2015).

[15] Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. 2025. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948* (2025).

[16] Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. 2022. Masked autoencoders are scalable vision learners. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 16000–16009.

[17] Jonathan Ho, Ajay Jain, and Pieter Abbeel. 2020. Denoising diffusion probabilistic models. *Advances in neural information processing systems* 33 (2020), 6840–6851.

[18] Yupeng Hou, Jiacheng Li, Zhankui He, An Yan, Xiusi Chen, and Julian McAuley. 2024. Bridging Language and Items for Retrieval and Recommendation. *arXiv preprint arXiv:2403.03952* (2024).

[19] Wenyue Hua, Shuyuan Xu, Yingqiang Ge, and Yongfeng Zhang. 2023. How to index item ids for recommendation foundation models. In *Proceedings of the Annual International ACM SIGIR Conference on Research and Development in Information Retrieval in the Asia Pacific Region*. 195–204.

[20] Bowen Jin, Hansi Zeng, Guoyin Wang, Xiusi Chen, Tianxin Wei, Ruirui Li, Zhengyang Wang, Zheng Li, Yang Li, Hanqing Lu, et al. 2023. Language models as semantic indexers. *arXiv preprint arXiv:2310.07815* (2023).

[21] Clark Mingxuan Ju, Leonardo Neves, Bhuvesh Kumar, Liam Collins, Tong Zhao, Yuwei Qiu, Qing Dou, Sohail Nizam, Sen Yang, and Neil Shah. 2025. Revisiting Self-attention for Cross-domain Sequential Recommendation. *arXiv preprint arXiv:2505.21811* (2025).

[22] Clark Mingxuan Ju, Leonardo Neves, Bhuvesh Kumar, Liam Collins, Tong Zhao, Yuwei Qiu, Qing Dou, Yang Zhou, Sohail Nizam, Rengim Aykan Ozturk, et al. 2025. Learning Universal User Representations Leveraging Cross-domain User Intent at Snapchat. In *Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 4345–4349.

[23] Mingxuan Ju, William Shiao, Zhichun Guo, Yanfang Ye, Yozen Liu, Neil Shah, and Tong Zhao. 2024. How Does Message Passing Improve Collaborative Filtering? *arXiv preprint arXiv:2404.08660* (2024).

[24] Mingxuan Ju, Wenhao Yu, Tong Zhao, Chuxu Zhang, and Yanfang Ye. 2022. Grape: Knowledge graph enhanced passage reader for open-domain question answering. *arXiv preprint arXiv:2210.02933* (2022).

[25] Mingxuan Ju, Tong Zhao, Qianlong Wen, Wenhao Yu, Neil Shah, Yanfang Ye, and Chuxu Zhang. 2022. Multi-task self-supervised graph neural networks enable stronger task generalization. *arXiv preprint arXiv:2210.02016* (2022).

[26] Wang-Cheng Kang and Julian McAuley. 2018. Self-attentive sequential recommendation. In *2018 IEEE international conference on data mining (ICDM)*. IEEE, 197–206.

[27] Dongmoon Kim, Kun-su Kim, Kyo-Hyun Park, Jee-Hyong Lee, and Keon Myung Lee. 2007. A music recommendation system with a dynamic k-means clustering algorithm. In *Sixth international conference on machine learning and applications (ICMLA 2007)*. IEEE, 399–403.

[28] Matthew Kolodner, Mingxuan Ju, Zihao Fan, Tong Zhao, Elham Ghazizadeh, Yan Wu, Neil Shah, and Yozen Liu. 2024. Robust training objectives improve embedding-based retrieval in industrial recommendation systems. *arXiv preprint arXiv:2409.14682* (2024).

[29] Yehuda Koren, Robert Bell, and Chris Volinsky. 2009. Matrix factorization techniques for recommender systems. *Computer* 42, 8 (2009), 30–37.

[30] Zhirui Kuai, Zuxu Chen, Huimu Wang, Mingming Li, Dadong Miao, Binbin Wang, Xusong Chen, Li Kuang, Yuxing Han, Jiaxing Wang, et al. 2024. Breaking the Hourglass Phenomenon of Residual Quantization: Enhancing the Upper Bound of Generative Retrieval. *arXiv preprint arXiv:2407.21488* (2024).

[31] Doyup Lee, Chiheon Kim, Saehoon Kim, Minsu Cho, and Wook-Shin Han. 2022. Autoregressive image generation using residual quantization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 11523–11532.

[32] Blerina Lika, Kostas Kolomvatsos, and Stathes Hadjiefthymiades. 2014. Facing the cold start problem in recommender systems. *Expert systems with applications* 41, 4 (2014), 2065–2073.

[33] Jianghao Lin, Xinyi Dai, Yunjia Xi, Weiwen Liu, Bo Chen, Hao Zhang, Yong Liu, Chuhan Wu, Xiangyang Li, Chenxu Zhu, et al. 2025. How can recommender systems benefit from large language models: A survey. *ACM Transactions on Information Systems* 43, 2 (2025), 1–47.

[34] Enze Liu, Bowen Zheng, Cheng Ling, Lantao Hu, Han Li, and Wayne Xin Zhao. 2024. End-to-End Learnable Item Tokenization for Generative Recommendation. *arXiv preprint arXiv:2409.05546* (2024).

[35] Zihan Liu, Yupeng Hou, and Julian McAuley. 2024. Multi-behavior generative recommendation. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*. 1575–1585.

[36] Donald Loveland, Mingxuan Ju, Tong Zhao, Neil Shah, and Danai Koutra. 2025. On the Role of Weight Decay in Collaborative Filtering: A Popularity Perspective. *arXiv preprint arXiv:2505.11318* (2025).

[37] Donald Loveland, Xinyi Wu, Tong Zhao, Danai Koutra, Neil Shah, and Mingxuan Ju. 2025. Understanding and Scaling Collaborative Filtering Optimization from the Perspective of Matrix Rank. In *Proceedings of the ACM on Web Conference 2025*. 436–449.

[38] Xinchen Luo, Jiangxia Cao, Tianyu Sun, Jinkai Yu, Rui Huang, Wei Yuan, Hezheng Lin, Yichen Zheng, Shiyao Wang, Qigen Hu, et al. 2024. QARM: Quantitative Alignment Multi-Modal Recommendation at Kuaishou. *arXiv preprint arXiv:2411.11739* (2024).

[39] Zhongyu Ouyang, Mingxuan Ju, Soroush Vosoughi, and Yanfang Ye. 2025. Non-parametric Graph Convolution for Re-ranking in Recommendation Systems. *arXiv preprint arXiv:2507.09969* (2025).

[40] Fabian Paischer, Liu Yang, Linfeng Liu, Shuai Shao, Kaveh Hassani, Jiacheng Li, Ricky Chen, Zhang Gabriel Li, Xialo Gao, Wei Shao, et al. 2024. Preference Discerning with LLM-Enhanced Generative Retrieval. *arXiv preprint arXiv:2412.08604* (2024).

[41] Fabian Paischer, Liu Yang, Linfeng Liu, Shuai Shao, Kaveh Hassani, Jiacheng Li, Ricky TQ Chen, Zhang Gabriel Li, Xiaoli Gao, Wei Shao, et al. [n. d.]. Preference Discerning in Generative Sequential Recommendation. ([n. d.]).

[42] Enrico Palumbo, Gustavo Penha, Andreas Damianou, José Luis Redondo García, Timothy Christopher Heath, Alice Wang, Hugues Bouchard, and Mounia Lalmas. 2025. Text2Tracks: Prompt-based Music Recommendation via Generative Retrieval. *arXiv preprint arXiv:2503.24193* (2025).

[43] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of machine learning research* 21, 140 (2020), 1–67.

[44] Shashank Rajput, Nikhil Mehta, Anima Singh, Raghunandan Hulikal Keshavan, Trung Vu, Lukasz Heldt, Lichan Hong, Yi Tay, Vinh Tran, Jonah Samost, et al. 2023. Recommender systems with generative retrieval. *Advances in Neural Information Processing Systems* 36 (2023), 10299–10315.

[45] Xubin Ren, Wei Wei, Lianghao Xia, Lixin Su, Suqi Cheng, Junfeng Wang, Dawei Yin, and Chao Huang. 2024. Representation learning with large language models for recommendation. In *Proceedings of the ACM Web Conference 2024*. 3464–3475.

[46] Steffen Rendle, Walid Krichene, Li Zhang, and John Anderson. 2020. Neural collaborative filtering vs. matrix factorization revisited. In *Proceedings of the 14th ACM Conference on Recommender Systems*. 240–248.

[47] Aravind Sankar, Yozen Liu, Jun Yu, and Neil Shah. 2021. Graph neural networks for friend ranking in large-scale social platforms. In *Proceedings of the Web Conference 2021*. 2535–2546.

[48] J Ben Schafer, Joseph Konstan, and John Riedl. 1999. Recommender systems in e-commerce. In *Procs. of ACM conference on Electronic commerce*.

[49] William Shiao, Mingxuan Ju, Zhichun Guo, Xin Chen, Evangelos E Papalexakis, Tong Zhao, Neil Shah, and Yozen Liu. 2025. Improving Out-of-Vocabulary Hashing in Recommendation Systems. In *Companion Proceedings of the ACM on Web Conference 2025*. 2521–2530.

[50] Anima Singh, Trung Vu, Nikhil Mehta, Raghunandan Keshavan, Maheswaran Sathiamoorthy, Yilin Zheng, Lichan Hong, Lukasz Heldt, Li Wei, Devansh Tandon, et al. 2024. Better generalization with semantic ids: A case study in ranking for recommendations. In *Proceedings of the 18th ACM Conference on Recommender Systems*. 1039–1044.

[51] Juntao Tan, Shuyuan Xu, Wenyue Hua, Yingqiang Ge, Zelong Li, and Yongfeng Zhang. 2024. Idgenrec: Llm-recsys alignment with textual id learning. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 355–364.

[52] Yi Tay, Vinh Tran, Mostafa Dehghani, Jianmo Ni, Dara Bahri, Harsh Mehta, Zhen Qin, Kai Hui, Zhe Zhao, Jai Gupta, et al. 2022. Transformer memory as a differentiable search index. *Advances in Neural Information Processing Systems* 35 (2022), 21831–21843.

[53] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971* (2023).

[54] Aaron Van Den Oord, Oriol Vinyals, et al. 2017. Neural discrete representation learning. *Advances in neural information processing systems* 30 (2017).

[55] Manasi Vartak, Arvind Thiagarajan, Conrado Miranda, Jeshua Bratman, and Hugo Larochelle. 2017. A meta-learning perspective on cold-start recommendations for items. *Advances in neural information processing systems* 30 (2017).

[56] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems* 30 (2017).

[57] Wenjie Wang, Honghui Bao, Xinyu Lin, Jizhi Zhang, Yongqi Li, Fuli Feng, See-Kiong Ng, and Tat-Seng Chua. 2024. Learnable item tokenization for generative recommendation. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*. 2400–2409.

[58] Kilian Weinberger, Anirban Dasgupta, John Langford, Alex Smola, and Josh Attenberg. 2009. Feature hashing for large scale multitask learning. In *Proceedings of the 26th annual international conference on machine learning*. 1113–1120.

[59] Xinyi Wu, Donald Loveland, Runjin Chen, Yozen Liu, Xin Chen, Leonardo Neves, Ali Jadbabaie, Mingxuan Ju, Neil Shah, and Tong Zhao. 2025. GraphHash: Graph Clustering Enables Parameter Efficiency in Recommender Systems. In *Proceedings of the ACM on Web Conference 2025*. 357–369.

[60] Longtao Xiao, Haozhao Wang, Cheng Wang, Linfei Ji, Yifan Wang, Jieming Zhu, Zhenhua Dong, Rui Zhang, and Ruixuan Li. 2025. Progressive Collaborative and Semantic Knowledge Fusion for Generative Recommendation. *arXiv preprint arXiv:2502.06269* (2025).

[61] Liu Yang, Fabian Paischer, Kaveh Hassani, Jiacheng Li, Shuai Shao, Zhang Gabriel Li, Yun He, Xue Feng, Nima Noorshams, Sem Park, et al. 2024. Unifying Generative and Dense Retrieval for Sequential Recommendation. *arXiv preprint arXiv:2411.18814* (2024).

[62] Yuhao Yang, Zhi Ji, Zhaopeng Li, Yi Li, Zhonglin Mo, Yue Ding, Kai Chen, Zijian Zhang, Jie Li, Shuanglong Li, et al. 2025. Sparse meets dense: Unified generative recommendations with cascaded sparse-dense representations. *arXiv preprint arXiv:2503.02453* (2025).

[63] Wenhao Yu, Dan Iter, Shuohang Wang, Yichong Xu, Mingxuan Ju, Soumya Sanyal, Chenguang Zhu, Michael Zeng, and Meng Jiang. 2022. Generate rather than retrieve: Large language models are strong context generators. *arXiv preprint arXiv:2209.10063* (2022).

[64] Zheng Yuan, Fajie Yuan, Yu Song, Youhua Li, Junchen Fu, Fei Yang, Yunzhu Pan, and Yongxin Ni. 2023. Where to go next for recommender systems? id-vs. modality-based recommender models revisited. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2639–2649.

[65] Caojin Zhang, Yicun Liu, Yuanpu Xie, Sofia Ira Ktena, Alykhan Tejani, Akshay Gupta, Pranay K. Myana, Deepak Dilipkumar, Suvadip Paul, Ikuhiro Ihara, Prasang Upadhyaya, Ferenc Huszár, and Wenzhe Shi. 2020. Model Size Reduction Using Frequency Based Double Hashing for Recommender Systems. In *Proceedings of the 14th ACM Conference on Recommender Systems*.

[66] Zihuai Zhao, Wenqi Fan, Jiatong Li, Yunqing Liu, Xiaowei Mei, Yiqi Wang, Zhen Wen, Fei Wang, Xiangyu Zhao, Jiliang Tang, et al. 2024. Recommender systems in the era of large language models (llms). *IEEE Transactions on Knowledge and Data Engineering* (2024).

[67] Zhe Zhao, Lichan Hong, Li Wei, Jilin Chen, Aniruddh Nath, Shawn Andrews, Aditee Kumthekar, Maheswaran Sathiamoorthy, Xinyang Yi, and Ed Chi. 2019. Recommending what video to watch next: a multitask ranking system. In *Proceedings of the 13th ACM conference on recommender systems*. 43–51.

[68] Bowen Zheng, Yupeng Hou, Hongyu Lu, Yu Chen, Wayne Xin Zhao, Ming Chen, and Ji-Rong Wen. 2024. Adapting large language models by integrating collaborative semantics for recommendation. In *2024 IEEE 40th International Conference on Data Engineering (ICDE)*. IEEE, 1435–1448.

[69] Bowen Zheng, Enze Liu, Zhongfu Chen, Zhongrui Ma, Yue Wang, Wayne Xin Zhao, and Ji-Rong Wen. 2025. Pre-training Generative Recommender with Multi-Identifier Item Tokenization. *arXiv preprint arXiv:2504.04400* (2025).

[70] Bowen Zheng, Hongyu Lu, Yu Chen, Wayne Xin Zhao, and Ji-Rong Wen. 2025. Universal Item Tokenization for Transferable Generative Recommendation. *arXiv preprint arXiv:2504.04405* (2025).

[71] Peilin Zhou, You-Liang Huang, Yueqi Xie, Jingqi Gao, Shoujin Wang, Jae Boum Kim, and Sunghun Kim. 2024. Is contrastive learning necessary? a study of data augmentation vs contrastive learning in sequential recommendation. In *Proceedings of the ACM Web Conference 2024*. 3854–3863.

[72] Jieming Zhu, Mengqun Jin, Qijiong Liu, Zexuan Qiu, Zhenhua Dong, and Xiu Li. 2024. CoST: Contrastive Quantization based Semantic Tokenization for Generative Recommendation. In *Proceedings of the 18th ACM Conference on Recommender Systems*. 969–974.

[73] Jing Zhu, Mingxuan Ju, Yozen Liu, Danai Koutra, Neil Shah, and Tong Zhao. 2025. Beyond Unimodal Boundaries: Generative Recommendation with Multimodal Semantics. *arXiv preprint arXiv:2503.23333* (2025).

[74] Yongxin Zhu, Bocheng Li, Yifei Xin, and Linli Xu. 2024. Addressing representation collapse in vector quantized models with one linear layer. *arXiv preprint arXiv:2411.02038* (2024).